PART 3

Toward More Productive Food Systems

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Productivity is key to ensuring the food system can provide a healthy diet for all. In past approaches to agricultural and rural development, much of the focus has been on improving food supply through the uptake of on-farm technologies. While the food systems approach takes a broader perspective, improving food production is still fundamental to driving transformation. Part 3 looks at agricultural productivity in Kenya, its evolution, and policies to improve it.

Agricultural production in Kenya is not uniform: the diversity of the country's agroecological zones means that productivity drivers and trends can differ by location, as Chapters 6 and 7 show. Chapter 6 analyzes the total factor productivity of Kenyan farms, and the question of whether to promote smallholder-dominated agricultural systems or systems based on larger farms. On the one hand, evidence suggests smaller farms are more efficient; on the other hand, small farmers face more barriers to market access, which can erode their efficiency gains. Chapter 7 shows that maize productivity, in particular, has stagnated in the past few decades, pointing toward a tapering-off of the Green Revolution. To reverse these trends, the chapter recommends boosting on-farm technology by including farmers in variety evaluations and by improving extension services. Further, market-based interventions, such as promoting private sector competition with the parastatal Kenya Seed Company, could boost adoption and lead to higher maize productivity.

Chapters 8 and 9 focus specifically on agricultural inputs and mechanization to drive productivity. Chapter 8 discusses trends, policies, challenges, and lessons learned from fertilizer, seed, pesticide, and knowledge usage. It highlights the need to improve market access to inputs through better transportation infrastructure, reduced regulations and levies, and promotion of the private sector. In particular, the use of input subsidies may crowd out private sector involvement in the input sector. Chapter 9 shows that mechanization faces slightly different challenges, related to the high fixed costs involved in adopting mechanized production techniques. Mechanization rates in Kenya remain low, partly because of the large portion of smallholder farmers in Kenya and the country's diverse agroecological conditions. In terms of policy, successful mechanization efforts in other countries have relied on the private sector, with the government playing a facilitating role. Promoting hiring services may help overcome the challenges involved in smallholder adoption of mechanization by removing the high fixed costs in accessing machinery. Further, policy can support the local manufacturing of machinery parts that are optimal for Kenyan farms. This could also be an important steppingstone toward full-scale machinery production in Kenya.

In summary, Part 3 looks at the many challenges to increasing agricultural productivity in Kenya. Solutions here must address the diverse agroecological landscape of Kenya and include a coherent plan on whether and how to promote a smallholder-driven transformation or a transformation focused on large-scale, commercialized farmers—or potentially both in parallel. Further, the role of market access in stimulating productivity is not to be understated; the book will return to this issue in Chapter 18, which discusses digital technologies.

Chapter 6

AGRICULTURAL PRODUCTIVITY IN KENYA, 2000–2020

Alejandro Nin-Pratt

Agriculture is key to economic growth and poverty reduction in Kenya as it plays a pivotal role in employment creation, food security, exports, and sustainable development. In 2019, it directly contributed 22.7 percent of GDP, accounted for 20.9 percent of total exports, and generated 43.3 percent of employment (Chapter 2). The sector is thus not only an important driver of Kenya's economy but also the means of livelihood for many Kenyan people.

Given the economic and social importance of agriculture in Kenya, policies have revolved around the main goal of increasing productivity and incomes, especially for smallholders, to enhance food security and equity, with an emphasis on production intensification, commercialization, and environmental sustainability (Alila and Atieno 2006). In this context, the declining performance of the sector measured in terms of its growth has been a major concern for policymakers.

This chapter looks at the performance of agriculture in Kenya—the first link in the food system chain of activities—in the context of the agricultural development strategies that the Government of Kenya has implemented since the year 2000. This entails the analysis of trends and of the evolution of output and total factor productivity (TFP) at the country level and a comparison of TFP and the technical efficiency of sub-counties with a focus on the Central Highlands, Rift Valley, and Western agroecologies. These zones contribute more than two-thirds of Kenya's agricultural output. Productivity is measured using a TFP index calculated using secondary data from the Kenya National Bureau of Statistics (KNBS). The regional analysis employs a decomposition of TFP into different measures of efficiency.

The chapter is organized as follows. The next section reviews the Kenyan agricultural policy context and the consequent productivity from independence to the present day. The chapter then lays out the methodology and data used to calculate TFP and to analyze production efficiency, followed by an analysis of output, input, and productivity trends in Kenya's agriculture sector between 2000 and 2020. After this, an efficiency analysis of the agricultural production of sub-counties in the Western, Central Highland, and Rift Valley zones is presented. The last section discusses alternative interpretations of the results obtained, with implications for Kenya's food security and agricultural policies.

An overview of agricultural policy and productivity in Kenya

Three distinct periods of policy and rural development can be observed between independence, achieved in 1963, and the year 2000, according to Kirori (2003) and Mwega and Ndung'u (2008). The 1960s saw enhanced flows of foreign direct investment, supported by import substitution policies for industrialization that were adopted before independence and deepened during this period. Simultaneously, the opening of the White Highlands in 1961, an area in the central uplands of Kenya that had officially been reserved for the exclusive use of Europeans, indirectly increased access to land. These two developments combined to enhance the productive capacity of agriculture, delivering relatively high economic growth but at the expense of increased regional inequality (Mwega and Ndung'u 2008). Between 1961 and 1972, Kenya's GDP per person grew at 3.0 percent on average as a result of the high GDP growth (7.2 percent); the average annual agricultural growth rate was 6.9 percent during the same period (World Bank 2022).

The second period extends from the late 1970s and to the mid-1990s. It opened with President Moi's election and the introduction of policies to address regional disparities (Mwega and Ndung'u 2008). This period was preceded by a series of exogenous shocks that eroded the performance of Kenya's economy. These included the oil crisis of the 1970s and the consequent world recession, high external interest rates and a decline in capital inflows, severe droughts, and the collapse of the East African Community in 1977, which soured the market for Kenya's nontraditional exports (Onjala 2002). Under Moi's regime, weaker budget management and the introduction of policies to control inflationary pressures that later created distortions in the economy were associated with a lower growth trajectory.

This situation lingered on until the early 2000s, slowing production expansion in both firms and smallholder farms, and overall economic growth (Mwega and Ndung'u 2008). Average annual GDP and agricultural GDP growth between 1973 and 1995 dropped to 4.0 and 3.2 percent, respectively. Slower growth together with fast population expansion resulted in an annual growth rate of GDP per person of only 0.5 percent.

The third period corresponds to the 1990s. It was characterized by economic reforms to aid markets to work better. During this period, Kenya shifted its economic development strategy from import substitution to export promotion and trade openness, significantly reducing restrictions on international trade and actively engaging in regional and continental integration initiatives. These reforms were instituted to reactivate the economy in response to declining growth. They included price decontrols, the removal of tariff and nontariff barriers, and the adoption of export promotion initiatives, including manufacturing in export processing zones, investment incentives, and increasing export market access through regional integration and bilateral trade agreements (Kenya, Ministry of Agriculture 2010; Wamalwa and Were 2021).

By the new millennium, most markets were fully liberalized, but these measures were often subject to reversal. Moreover, the impact of liberalization was not immediate (Kimenyi, Mwega, and Ndung'u 2015). Between 1995 and 2002, years of economic transformation in Kenya, GDP and agricultural GDP increased at approximately 2.0 percent annually, whereas GDP per person shrank at an average rate of −0.7 percent (World Bank 2022).In addition, between 1993 and 2000, the export sector performed poorly even for commodity exports such as tea, coffee, and horticulture, in which Kenya has a comparative advantage.

A study by Nyoro and Jayne (1999) looked at the changes undergone by the agriculture sector in Kenya after the implementation of structural adjustment and sectoral reform programs in the 1990s. It found a decline in labor productivity of about 20 percent between 1970/74 and 1990/94, while land productivity had increased up to about 1990 and fallen in the last years of the analyzed period. The authors also found that large increases in land and labor productivity in the most productive areas (the then-Central province) reflected changes in the crop mix, with a significant expansion of the area allocated to crops like coffee, tea, maize, and wheat, together with the introduction of new varieties of maize and wheat. In low-potential areas, on the other hand, crop yields had declined because of a lack of enhanced technologies adapted to those areas.

In the year 2000, Kenya's economy recorded an all-time low growth rate of 0.6 percent. However, following a peaceful change of government in December 2002 from the Kenya African National Union, which had ruled the country since independence, to the National Rainbow Coalition under Mwai Kibaki, the growth rate accelerated (Kimenyi, Mwega, and Ndung'u 2015).

In 2003, the new government launched the Economic Recovery Strategy for Wealth and Employment Creation (ERS; 2003–2007) as the blueprint for setting the country back on a growth path. The ERS focused on agriculture, trade and industry, and tourism as the key sectors to drive the economic recovery and contribute to improving food security and reducing rural poverty. The Strategy for Revitalizing Agriculture (SRA) followed in 2004, to "transform Kenya's agriculture into a profitable, commercially oriented and internationally and regionally competitive economic activity," providing an enabling environment for increasing agricultural productivity, promoting investment, and encouraging private sector involvement in agriculture. The overall aim was to refocus the government on the provision of key public goods, such as research and extension services, roads, and irrigation infrastructure (Poulton and Kanyinga 2014).

Significant progress was made during the ERS period. The economy recovered from low growth of 2.0 percent in 1995–2000 to growth of 5.5 percent between 2003 and 2007 (World Bank 2022). As a result, real per capita income increased at an annual average rate of 2.4 percent. In theory, these changes ought to have benefited agricultural producers, but this did not happen, at least at the aggregated sectoral level, despite the priority the government attached to agricultural recovery and the support the SRA received from Kenya's international development partners. Average annual agricultural growth of 0.9 percent between 2003 and 2007 was well below overall GDP growth (World Bank 2022).

There were, however, improvements in some subsectors. Kibaara and colleagues (2008), analyzing trends in crop yields using household panel survey data from eight agro-regional zones between 1996/97 and 2006/07, found consistent growth in maize productivity across most zones. This was driven by an increased percentage of households using fertilizer and high-yielding crop varieties, coinciding with an increased density of fertilizer retail outlets and a decline in the distances between farmers and sellers of agricultural inputs. Their findings also showed impressive growth of the dairy subsector as a result of increased production of fodder crops and the adoption of improved cattle breeds.

Meanwhile, Kibaara and colleagues found that tea yields had grown slightly, driven by increased fertilizer use, while the productivity of sugarcane and coffee had declined during the decade. These results on the productivity of export crops confirm findings showing that, while growth of nominal exports increased from an average rate of 4.1 percent in 1990–1999 to 11 percent in

2000–2009, during a period of fast-growing commodity prices, the actual growth of export quantities was only 1.6 percent in the latter period, compared with 2.8 percent growth in imports. This widened the trade gap and was a drag on economic growth, which was heavily dependent on the domestic market (Wamalwa and Were 2021).

The elections held in 2007 marked a new phase in Kenya's policy and development context. They were followed by a serious outbreak of ethnic violence, drought, and the global financial crisis, which eroded the achievements of the previous half-decade. There was significant disruption to the economy, which grew only 0.23 percent in 2008 (Kimenyi, Mwega, and Ndung'u 2015). After a year-long political crisis, and with the ERS set to expire, in June 2008 the newly elected government launched the Kenya Vision 2030 as the new long-term development blueprint for the country, with a vision of transforming Kenya into "a globally competitive and prosperous country with a high quality of life by 2030" (Kenya, Ministry of State Planning 2007). The SRA was revised to capture new developments and to strategically position the agriculture sector as a key driver in delivering the 10 percent annual economic growth rate envisaged under the economic pillar of Vision 2030.

The Agricultural Sector Development Strategy (ASDS) 2010–2020 aimed to deliver the Millennium Development Goal targets, with the main objective of achieving a food-secure and prosperous nation by 2020 through the transformation of smallholder agriculture from subsistence to commercially oriented and modern approaches. The new strategy identified four major challenges to Kenyan agriculture: persistent low productivity; suboptimal land use, mainly related to the growth of the population; inefficient markets owing to insufficient storage capacity and poor access; and low levels of value addition and largely informal value chains. The ASDS provided the basis for the implementation of the Comprehensive Africa Agriculture Development Program (CAADP) Compact and the formulation of the Medium-Term Implementation Plan (MTIP) 2010–2015.

The Government of Kenya developed its latest strategy, the Agricultural Sector Transformation and Growth Strategy (ASTGS, Kenya, Ministry of Agriculture 2018), and the National Agricultural Investment Plan (NAIP) after 2015, faced with suboptimal performance of agriculture in terms of production, value addition, food security, and nutrition. The new strategy was anchored in the belief that food security requires a vibrant, commercial, and modern agriculture sector that sustainably supports economic development, national priorities, and commitments to the Malabo Declaration under CAADP and the UN Sustainable Development Goals. The ASTGS divides the country into seven distinct agroecological zones based on soil type and rainfall and uses this division as the basis for value chain and intervention selections, to ensure the latter are sensitive to the needs of farmers in these areas.

Decades of policy changes were finally reflected in the country's economic performance after 2015. Data from the World Bank (2022) show that Kenya's economy achieved broad-based growth between 2015 and 2019, with GDP growth averaging 4.9 percent per year. Poverty declined significantly, falling to an estimated 34.4 percent at the $1.90/day line in 2019 (World Bank 2023). In 2020, the COVID-19 pandemic hit the economy hard, disrupting international trade and transport, tourism, and urban services activity. Fortunately, the agriculture sector, a cornerstone of the economy, remained resilient, helping limit the pandemic-driven contraction in GDP to only 0.3 percent (World Bank 2023).

Despite progress made, there are still signs that Kenya's agriculture sector is not yet on a sustainable path of fast growth driven by TFP. For example, De Groote (2022), using 2022 data from the Food and Agriculture Organization of the United Nations (FAO), on the area, production, and yield of maize between 1961 and 2022, shows that Kenya has not been able to sustain growth in maize productivity. While maize yields almost doubled between 1961 and the mid-1980s, they have remained stagnant for the past 30 years, with output growth driven by area expansion. If this is the case for most agricultural subsectors, it will be important to look again at Kenya's agricultural productivity growth to analyze the impact of policy changes after the economic transformation of the 1990s and the new policies and strategies implemented between 2000 and 2020.

In a review of the literature on agricultural productivity in Kenya, Birch (2018) identified some of the principal barriers to agricultural productivity growth, clustered in different areas:

- Land and population pressures mean that average farm size is falling and land is becoming more concentrated. Ever-smaller farm sizes may undermine the capacity of households to generate a surplus and the economic incentive to invest to improve productivity.

- Government interventions in markets distort input and cereal markets; and institutional barriers, high transaction costs, and limited access to credit further hamper markets.

- Low adoption of sustainable land management practices leads to increasing land degradation, and changes in temperature and variability of rainfall pose a growing threat to agricultural production (see, for example, De Groote and Omondi 2021; Jena et al. 2021).

- Public expenditure on agriculture is low, and spending on agricultural research in particular has fallen steadily over the past decade, by 2016 declining to one-third of its value in 2006 (Beintema et al. 2018). Low spending has also resulted in insufficient qualified personnel in extension services, with a ratio of national extension staff to farmers at 1:1,000, compared with the recommended 1:400 (Wanyama et al. 2016, 23).

Approach

The approach to calculating TFP and the data used are described in this section. The calculation of TFP used at the aggregated country level and in the regional comparison at the sub-county level follows O'Donnell (2012) in that TFP is expressed as the ratio of an index of total output and an index of total input based on a simple linear aggregation of inputs and outputs. O'Donnell refers to this index as the Lowe index of TFP, one of the indexes in a class of TFP indexes that are particularly suited to intertemporal and cross-sectional comparisons of production units (farms, counties, countries). Starting with the analysis of aggregated agricultural productivity across time, calculation of the TFP index to measure productivity changes between 2000 and 2020 involves the calculation of total output and input quantity indexes and the total output–input ratio for each year. For example, the change in agricultural TFP in Kenya between 2000 and 2020 can be expressed as $TFP_{2000\text{-}2020}=(QI_{2000\text{-}2020}/XI_{2000\text{-}2020})$, where $QI_{2000\text{-}2020}$ and $XI_{2000\text{-}2020}$ are the changes in aggregated output and total aggregated input between 2000 and 2020, respectively. More formally, the TFP index between period t and a reference period s is expressed as the ratio of an output index (QI) and an input index (XI):

$$MFP_{st} = \frac{QI_{st}}{XI_{st}} = \frac{Q(q_t)}{Q(q_s)} \div \frac{X(x_t)}{X(x_s)} \qquad 1$$

where $Q(q_t)$ is the weighted sum of m outputs produced in year t: $Q(q_t)=\sum_m p_m q_{mt}$ and $X(x_t)=\sum_n w_n x_{nt}$ is the weighted sum of n inputs used in production in the same year, with p_m and w_n being predetermined time-invariant reference prices of outputs and inputs, respectively. In the case of sub-county comparisons in the same year, the index is calculated in the same way but, instead of comparing TFP between periods s and t, the comparison is between the sub-county of interest A and the reference sub-county h:

$$MFP_{Ah} = \frac{QI_{Ah}}{XI_{Ah}} = \frac{Q(q_A)}{Q(q_h)} \div \frac{X(x_h)}{X(x_A)} \qquad 2$$

These indexes are ratios of the values of baskets of outputs and inputs from sub-counties A and h evaluated at the same set of reference prices. Note that the same prices are used to build the output and input indexes in all years for the country-level analysis. Similarly, for the cross-sectional analysis, the same prices are used to calculate output and input indexes for each sub-county. O'Donnell (2012) recommends the use of price vectors that are representative of the price vectors facing all production units that are to be compared.

The spatial analysis of the performance of agricultural production is conducted by clustering sub-counties into groups with the same or a similar agroecology and production environment, and comparing all sub-counties against the sub-county with the highest TFP value in each group. The performance of agriculture at the sub-county level is analyzed by measuring TFP efficiency (*TFPE*) for each sub-county. A measure of *TFPE* for sub-county A is defined as the ratio of A's *TFP* and the *TFP* of the most productive sub-county in its group (TFP^*).

$$TFPE_A = TFP_A / TFP^* \qquad 3$$

The maximum value of *TFPE* is 1, only obtained if A is the sub-county with the highest *TFP* (*TFPA=TFP**). Using the definition of efficiency, unit A's *TFP* can then be expressed as the product of the maximum observed *TFP* and *TFP* efficiency:

$$TFP_A = TFP^* \times TFPE_A \qquad 4$$

Differences between sub-counties and the most productive sub-county in each group in a particular year are the result of inefficiency in the use of inputs.[1] For this purpose, the *TFP* index in Equation 2 comparing sub-counties A and h can be exhaustively decomposed into different measures of efficiency. As O'Donnell (2012) shows, total *TFPE* of a production unit can be decomposed into different measures of efficiency by changing the reference efficient production unit used in the comparison. The intuition of this decomposition and the different efficiency measures follows. A more formal approach to this decomposition can be found in Appendix 6.1.

1 If comparisons of performance were conducted across sub-counties and years, then the maximum value of TFP in each group could potentially change between periods as the result of technical change. In this case, differences in TFP levels result from differences in efficiency and in the level of technology used. Inefficient sub-counties could increase TFP as the result of technical change (the shift of the technological frontier expressed as a change in the maximum value of TFP) and by increasing efficiency (reducing the difference between their own TFP and the maximum TFP). In this chapter, comparisons between sub-counties are conducted for the year 2019, so differences in TFP between sub-counties are explained by differences in efficiency in the use of the available technology in that particular year.

One of the possible decompositions of *TFPE* proposed by O'Donnell (2012) is:

$$TFPE_A = TE_A \times ME_A \times RSE_A \qquad 5$$

where *TFPE* is *TFP* efficiency of production unit (sub-county) *A*, as defined in Equation 3; *TE* is "pure" technical efficiency; *ME* is mix efficiency; and *RSE* is residual scale economy efficiency. TE_A is obtained by comparing production unit *A* with production units using the same combination of inputs to produce the same combination and amount of outputs as *A*. TE_A is referred to as "pure" technical efficiency because differences between *A* and the reference production unit are not related to differences in the output or input mix, nor to the scale of production, but only to the differences in management of the same combination of inputs and outputs. A value of $TE_A<1$ means that output produced by *A* can be obtained with the same input mix and a smaller quantity of aggregated input than the one used by *A*.

The measure of mix efficiency (ME_A) is obtained by comparing production unit *A* with units producing the same quantity of aggregated output as *A* but with different input mixes than the one used by *A*. A value of $ME_A<1$ indicates that it is feasible to produce the same quantity of aggregated output as A using less inputs by using a different input mix.

Notice that, to improve *ME*, unit *A* can change the mix of inputs to further reduce the aggregated level of inputs used to produce the original level and mix of aggregated outputs (Q_A). However, it is still possible to further increase *TFPE* if *A* is allowed to change the level of aggregated output. For example, a higher or a lower level of aggregated output with a different output mix than the one used by *A* could result in higher *TFP* than the one obtained with the level of output produced by *A*. This is captured by the last term in Equation 5, reflecting differences in scale between unit *A* and the unit with the highest *TFP*. However, *RSE* is not a measure of "pure" scale efficiency because it is calculated as a residual and reflects differences in scale and in the mix of inputs between *A* and the most efficient production unit.

O'Donnell (2012) also defines an alternative decomposition of *TFPE* that includes a measure of pure scale efficiency (*SE*) instead of *ME*. In this decomposition, the residual term is a residual mix efficiency (*RME*) and the *TE* is the same as in Equation 5:

$$TFPE_A = TE_A \times SE_A \times RME_A \qquad 6$$

To obtain *SE*, production unit *A* is compared with production units obtaining the same level of aggregated output but using different levels of aggregated input with the same input mix as *A*. If *SEA<1*, production unit *A* can increase productivity by proportionally increasing (or reducing) the total level of input. This is "pure scale" efficiency because no differences in the mix of inputs are involved. Unlike *ME*, *RME* is not a measure of "pure" mix efficiency because it is calculated as a residual and results from differences in the input mix and in the level of output between *A* and the most efficient production unit.

Data

Agricultural TFP at the country level was calculated using data on total output, materials, agricultural land, irrigated land, labor, animal stock, and machinery. Definitions and sources of the variables used are as follows:

Output: An agricultural output and input series in millions of current and constant Kenyan shillings for the period 2000–2020 was obtained from several issues of the KNBS Economic Survey, published annually. An index of output prices was built using Kenya's producer prices from FAO (2022) in current Kenyan shillings for the analyzed period. Prices of individual commodities were aggregated into a price index using average quantities of each commodity for the period.

Materials: Values of materials and input services used in production and their respective price indexes were also obtained from the KNBS Economic Survey. Materials include fertilizers, other chemicals, livestock drugs and medicines, fuel, power, spares and maintenance of machinery, bags, manufactured feeds, seeds, and others. Input services include artificial insemination, aerial spraying, tractor services, private veterinary services, and government veterinary inoculation services. Values were converted into quantities and aggregated into a single input (materials) that includes input services.

Land: Cultivated land for the year 2019 was obtained from the 2019 Kenya Population and Housing Census: Volume IV. Using 2019 as the reference, a timeseries for the period 2000–2020 was built using data on cropland from FAO (2022). The price of land used as weight to include land in the aggregate input index is from the Kenya Integrated Household Budget Survey (KIHBS) 2005/06. The KIHBS collected data on the cost of land in various regions and used this information to compute the median sale price of an acre of farmland and the cost of renting or leasing land parcels over the 12 months preceding the survey at the county level. The median price for renting/leasing an acre of land in rural areas for a year in Kenya was KSh 2,000, with the lowest value of KSh 333 in Mwingi and a high of KSh 9,600 in Isiolo.

Labor: Employment in Kenya is categorized into three sectors—namely, formal (modern), informal, and small-scale agriculture or subsistence farming and pastoralist activities. The KNBS Economic Survey keeps track of employment in the first two categories but no information was found on small-scale agriculture and pastoralists. To build the labor series, information on the number of households farming and on the total number of people employed by sub-county working from the 2019 Census was used. The total number of workers in each sub-county was allocated to agriculture proportionally to the number of households farming. Annual data for 2000–2020 were built using share of total employment in agriculture and total employment from the World Bank (2022). Labor prices used in the aggregate input index are wage earning per employee per year (in Kenyan shillings) in formal agriculture from the KNBS Economic Survey (several issues).

Animal stock: A similar approach to the one used for land was used to build the total animal stock series. Detailed information at the sub-county level on the number of heads of beef and dairy cattle, sheep, goats, camels, chickens, and pigs was obtained from the 2019 Census and used as a reference to build the time series for the period 2000–2020 using data on animal stock from FAO (2022). Average prices per ton of live weight in current Kenyan shillings from FAO (2022) were used to calculate the total value of the animal stock, and a real interest rate of 7 percent was used to determine the contribution of animal stock to total input.

Machinery: No data on mechanization are available from the Government of Kenya, including in the 2009 and 2019 Censuses. Information used on trends in tractor use was obtained from De Groote, Marangu, and Gitona (2020), who used four household surveys conducted between 1992 and 2012 to analyze the evolution of agricultural mechanization in Kenya. Number of tractors in World Bank (2023) was used to build the trend in machinery use after 2012. The flow of services from tractor use was calculated using the market price of an average tractor in Kenya to determine the total capital in tractors, and then a depreciation rate of 10 percent and an interest rate of 7 percent to establish the input from machinery to production.

Two major sources of information were used to build the dataset for the regional cross-sectional analysis at the sub-county level. The 2019 Kenya Population and Housing Census was the source of cultivated area, labor, and animal stock at the sub-county level by species. In the case of the animal stock, the number of heads of each species was converted to animal units (AUs) based on animal weights from FAO (2022). The total cultivated area by sub-county is also drawn from the 2019 Census. The number of workers in agriculture was calculated using the proportion of farming households and the total number of working persons per sub-county.

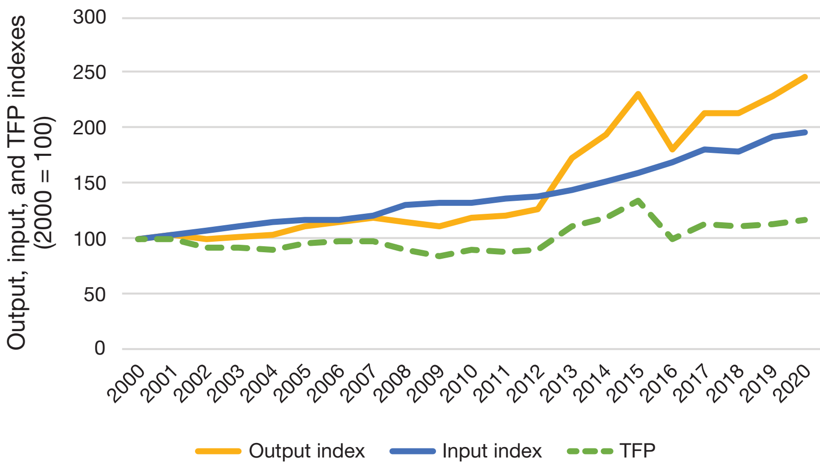
The second source of information was the Spatial Production Allocation Model (SPAM) (IFPRI 2020). This accesses a variety of information sources to generate plausible, disaggregated estimates of crop distribution, which are useful for understanding production and land use patterns. SPAM uses a variety of inputs together with a cross-entropy approach to make plausible estimates of crop distribution, moving the data from coarser units such as countries and subnational provinces to finer units such as grid cells at 10×10 km resolution, to create a grid for 42 crops and 2 production systems within disaggregated units. Grid cell data on harvested area, production, the value of production, and yields were aggregated to the sub-county level. The portion of rainfed and irrigated crops produced using "high inputs" was also calculated at the sub-county level and used to allocate total crop materials calculated at the country level.

Production values from SPAM were used to calculate the output shares of each sub-county in the total value of crop output so that the aggregate of the total value of production of sub-counties added up to the value of crop production from KNBS. Yields were then recalculated with the adjusted production values. Animal stocks by sub-county from the 2019 Census were used to allocate livestock production across sub-counties. The proportion of exotic dairy, beef, and poultry AUs in each sub-county was used as an indicator of "high inputs" use to allocate livestock materials across sub-counties. Livestock output was allocated based on total number of AUs in each sub-county adjusted by the proportion of exotic AUs, assuming that the larger the proportion of exotic animals, the larger the production per animal in the sub-county.

Production and productivity trends

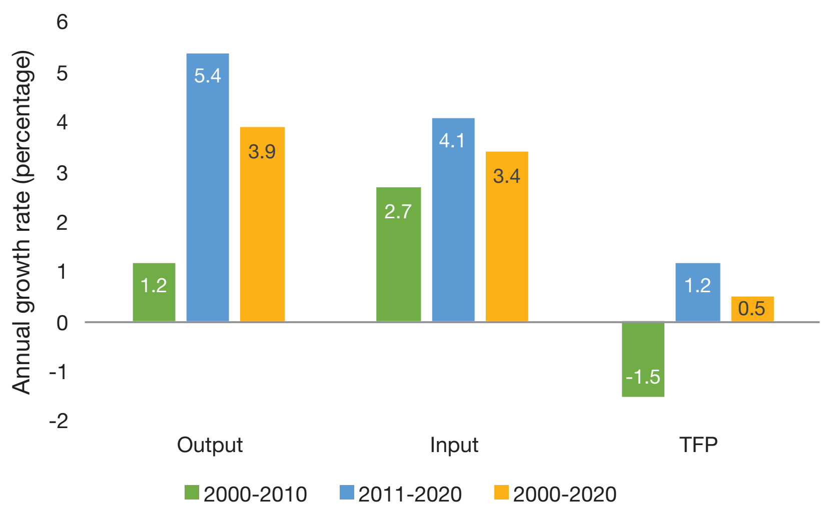
Policy changes since the year 2000 are reflected in the evolution and growth rates of agricultural output and its components, total input, and TFP (Figures 6.1 and 6.2). Figure 6.1 shows that the performance of agriculture between 2000 and 2007 was still poor after the country saw its lowest GDP growth in 2000, and policy changes of the 1990s and the SRA introduced under President Kibaki did not show an immediate impact. Output increased at an average annual rate of 1.2 percent, driven by input growth of 2.7 percent, resulting in negative growth of −1.5 percent (Figure 6.2). The poor performance of agriculture is explained in part by adverse climatic conditions during the period that negatively affected agricultural incomes and investments in rural areas (Balié et al. 2018). Mutsotso, Sichangi, and Makokha (2018) characterized the period between 1998 and 2001 as one of prolonged and moderate drought, and 2005 and 2006 as years of mild drought.

FIGURE 6.1 Evolution of agricultural production and output decomposition, 2000–2020



Source: Elaborated by authors based on KNBS (various years; 2006; and 2019), FAO (2022), and World Bank (2022).

FIGURE 6.2 Average growth rates of output, input, and TFP in different periods



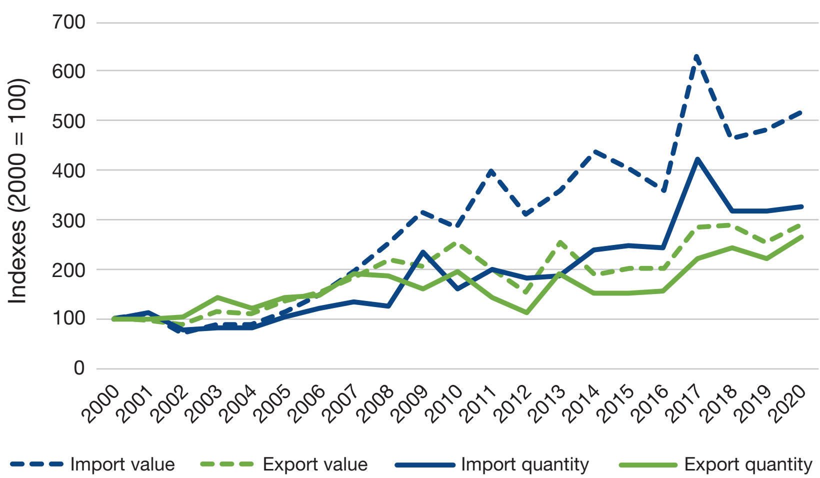
Source: Elaborated by authors based on KNBS (various years; 2006; and 2019), FAO (2022), and World Bank (2022).

The implementation of the ASDS after 2008 and the launch of the first MTIP 2008–2013 had to deal with the consequences of a prolonged severe drought between 2008 and 2011 (Mutsotso, Sichangi, and Makokha 2018), further delaying the expected positive effects of policy changes of previous years. Figure 6.2 shows that agricultural production started its recovery after 2010, and then grew at an average rate of 5.4 percent until 2020, with input growing at more than 4.0 percent annually and TFP reaching an average growth of 1.2 percent.

Is growth after 2012 an indication of a significant impact of policy changes since the 1990s, or is it mostly the result of the recovery of agriculture after the 2008–2011 drought and after the global economic slowdown? There is no definitive answer to this question, but some evidence suggests that agricultural growth patterns in recent years are not qualitatively different from growth observed before 2008. To show this, Figure 6.3 presents trends in the value of food exports and imports, and Figures 6.4 and 6.5 the evolution of input use and trends in, respectively, labor and land productivity.

Since 2010, Kenya has no longer been a surplus producer of food, as slow growth in agriculture and fast population growth have accelerated growth in imports of agricultural products (Figure 6.3). With the population projected to double between 2020 and 2050, food production and agricultural exports will need not only to sustain fast growth in the next 30 years but also to diversify

FIGURE 6.3 Evolution of the value and volume of agricultural imports and exports since 2000

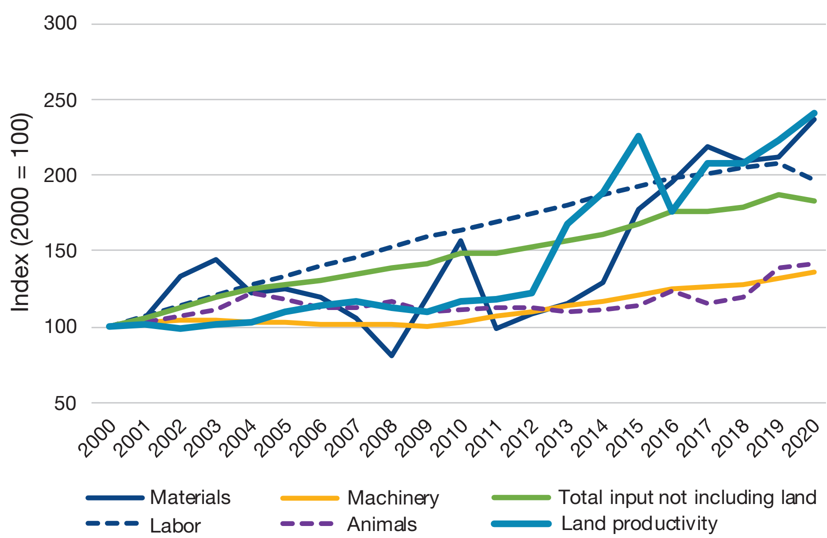


Source: Authors using data from FAO (2022).

and to increase value added in the case of agricultural exports. As Wamalwa and Were (2021) stress, Kenya's major agricultural exports like tea, coffee, and animal products, with low income elasticities, yield lower and volatile foreign earnings compared with higher-value agricultural exports and manufactures. Wamalwa and Were argue that the prevalence of primary commodities, low productivity externalities, and stiff competition from cheap exports from developing and emerging economies have contributed to the decline in competitiveness of Kenya's merchandise exports, as made evident by shrinking net merchandise exports to Africa, the Common Market for Eastern and Southern Africa (COMESA), and the East African Community since 2011. Kenya's loss of export competitiveness applies not only to African countries but also to the rest of the world.

The pattern of agricultural intensification observed in the past 10 years shows that increased production and productivity have been the result of intensive use of labor and materials per hectare of cropland. Figure 6.4 shows that land productivity more than doubled between 2012 and 2020 as a result of

FIGURE 6.4 **Trends in land productivity and use of inputs per hectare of cultivated land, 2000–2020**



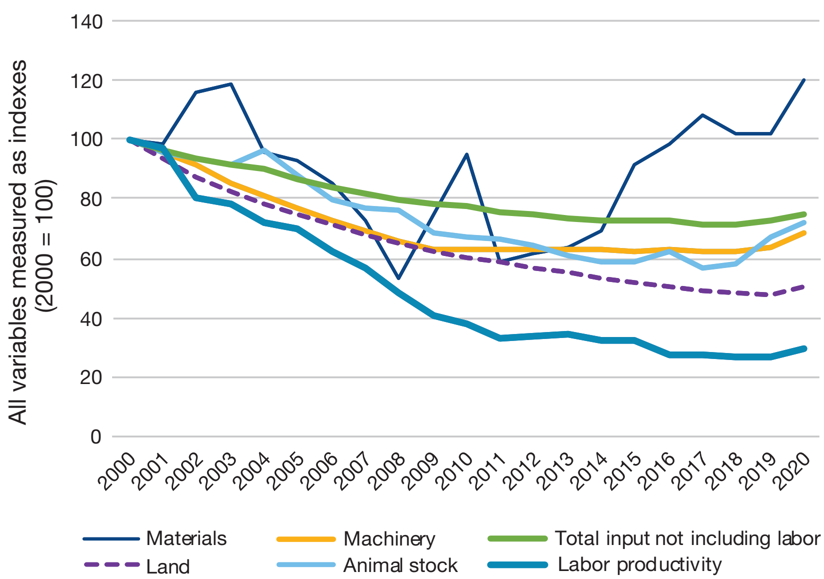
Source: Elaborated by authors based on KNBS (Various years; 2006; and 2019), FAO (2022), and World Bank (2022).

Note: Land productivity is measured as the ratio of agricultural output to land used in agriculture. Materials, labor, machinery, and animals refer to the ratio of each individual input to land used in agriculture. Total input not including land is calculated as the index of total input in the section on Approach and Data above, the difference being that land is not included.

sustained growth in the number of workers per hectare and a very large increase in the use of materials per hectare of cropland. Fertilizer was one of the major drivers of the observed growth in materials, explained in part by the introduction of a fertilizer subsidy program in 2006. As Jayne and colleagues (2018) point out, however, even though fertilizer subsidies can quickly raise national food production and grain yields at least in the short term, the overall production and welfare effects of subsidy programs tend to be smaller than expected. According to Jayne and colleagues, two characteristics of these programs consistently mitigate their intended effects. The first is that subsidy programs partially crowd out commercial fertilizer demand owing to difficulties associated with targeting and sale of inputs by program implementers. The second is that the crop yield response to fertilizer is lower than expected. Jayne and colleagues conclude that improved seed and fertilizer are not sufficient to achieve profitable and sustainable farming systems in most parts of Africa.

Increasing land productivity by relying mostly on increased fertilizer per worker and intensive use of labor per hectare, as observed in Kenya in recent years, has yet to yield benefits in terms of labor productivity. Despite the rapid

FIGURE 6.5 Trends in labor productivity and use of inputs per worker, 2000–2010



Source: Elaborated by authors based on KNBS (Various years; 2006; and 2019), FAO (2022), and World Bank (2022).

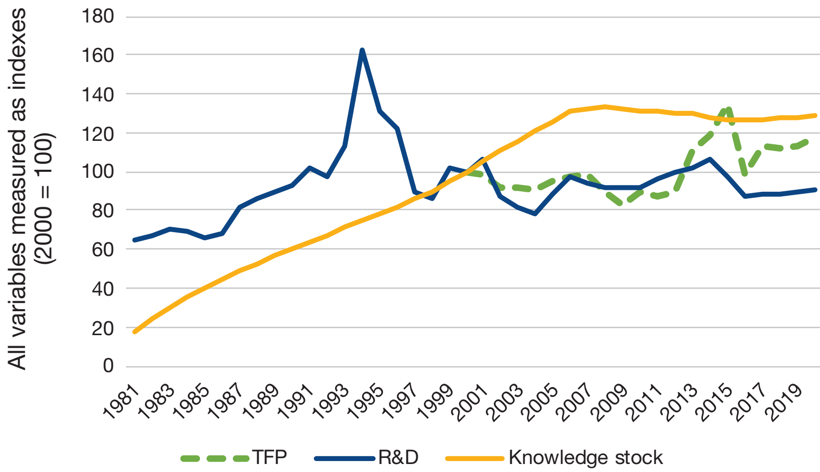
increase in the use of materials per worker, labor productivity in agriculture reached its lowest historical level after 2012 and has remained unchanged since that year (Figure 6.5). A study by De Groote, Marangu, and Gitonga (2020) on mechanization in Kenya using data for the period 1992–2012 shows persistently low levels of mechanization. According to this study, in 2012 most farm households still used only hand tools; from 1992 to 2012, the percentage of farmers with oxen increased from 17 to 33 percent but those with tractors decreased from 5 percent to 2 percent. No data on mechanization are available for recent years but De Groote, Marangu, and Gitonga conclude that mechanization in Kenya is likely to continue to depend on animal traction as it is not linked to farm size, complements labor, helps reduce fertilizer use, increases commercial maize production, and has room to grow—particularly in the highlands.

Policy changes in the past two decades have had some success in the medium run, improving the performance of agriculture and increasing the use of materials per hectare, land productivity, and TFP. However, in the long term, the key determinant of agricultural growth will be the growth in the stocks of productive capital and knowledge (agricultural research) affecting the productivity of land and labor in the production of agricultural goods. For this reason, the low public expenditure in agriculture that Birch (2018) notes—with spending on agricultural research falling steadily over the past decade—should be a concern regarding future growth in agriculture.

Figure 6.6 shows the evolution of public R&D investment in Kenya and the knowledge stock that agricultural research generates.[2] Note that the evolution of research spending is correlated with the policy changes discussed above. The peak of government spending in agricultural R&D occurred in 1994; it dropped sharply after that year in concert with policy changes favoring less government intervention, export promotion, and trade openness and remained stagnate after 2000. As a result, knowledge stock has not grown since 2012 and, because of the lagged effect of research (it takes several years for an investment to have an impact on productivity), even if Kenya increases R&D spending in the coming years it could take a decade or more for this to be reflected in faster productivity growth.

2 The knowledge stock can be thought of as the total knowledge accumulated as a result of past research. A measure of this knowledge in a particular year is obtained by adding up all R&D spent before that year (in this case going back 30 years). The contribution of investments on the path to the knowledge stock depends on how long ago the investment was made as knowledge generated in the past could become obsolete.

FIGURE 6.6 Evolution of public R&D investment in agriculture and of the knowledge stock from agricultural research, 1981–2019



Source: Elaborated by authors based on ASTI (2021).

Regional analysis of productivity and efficiency

The starting point for the regional analysis is the division into seven distinct agroecological zones based on soil type and rainfall as used in the ASTGS (Kenya, Ministry of Agriculture 2018) as the basis for value chain and intervention selections. Table 6.1 gives a brief description of the seven zones and Appendix 6.2 presents a general characterization of the seven zones, including information on Mombasa–Nairobi and total country values for comparisons.

The most important agricultural zones in Kenya for their production, their contribution to total output, and the number of people working in the sector are the Western and Central Highlands zones. More than 30 percent of Kenya's agricultural output, almost half of the people working in agriculture, 40 percent of total materials used, and about 30 percent of cropland are in the Western zone, the agroecology with the highest agricultural potential. As Table 6.1 shows, this region produces cereals and root crops (23 percent of regional output), fruits and vegetables (30 percent), and coffee and tea (15 percent). Dairy production (8 percent) is the main livestock activity. Pulses, oil crops, sugarcane, and other livestock products are also produced. The Central Highlands zone

TABLE 6.1 Characterization of agroecological zones

	Northern ASALs	Central ASALs	Semiarid Uplands	Coast	Rift Valley	Central Highlands	Western
Agricultural potential							
High potential land (%)	0	10	8	10	39	52	55
Poor potential land (%)	99	73	37	65	41	12	7
Length of growing period	106	200	183	181	253	227	286
Zone's share in total input use (%)							
Materials	10	10	13	3	10	14	40
Animal units	29	18	8	2	11	6	25
Cropland	12	10	19	6	14	10	29
Labor in agriculture	4	6	12	5	10	16	47
Zone's share in total output (%)							
Agriculture	6	10	13	7	7	23	33
Crops	2	7	13	9	5	28	37
Livestock	21	20	11	3	15	10	20
Output composition in each zone (%)							
Cereals	2	5	16	5	20	9	16
Roots and tubers	0	3	4	4	15	20	7
Pulses	1	3	27	1	6	9	9
Oil crops and sugarcane	1	1	0	3	0	0	8
Coffee and tea	0	0	2	0	3	18	15
Fruits and vegetables	15	39	28	76	4	34	30

Source: Elaborated by authors based on Kenya, Ministry of Agriculture (2018).

Note: High and poor potential land refers to the proportion of land that is classified as of high and poor potential within each zone, respectively. Input and output shares refer to the share of each zone in Kenya's total use of inputs and in total output. Output composition refers to the output mix produced by each zone.

also has high potential; it produces 23 percent of Kenya's total agricultural output, mostly cash crops like coffee and tea, roots and tubers (Irish potatoes), fruits and vegetables (French beans, bananas, tomatoes), and livestock.

Showing lower agricultural potential, the Rift Valley and Coastal zones contribute 7 percent each to total output. In the case of Rift Valley, the share of livestock production in total output is 50 percent. This zone also produces mixed staples (35 percent of regional output) and a smaller share of cash crops and fruits and vegetables. The Coastal zone, on the other hand, produces fruits and vegetables (76 percent of regional output), mixed staples (10 percent), and livestock (10 percent).

Finally, the arid and semiarid lands (ASALs) are the zones with the lowest potential for agriculture. Here, farming households are mostly pastoralists, raising beef cattle, goats, sheep, and camels, with occasional maize cultivation on raised plateaus. The northern ASALs have poorer infrastructure and are more remote from major markets compared with the central ASALs (see Appendix 6.2).

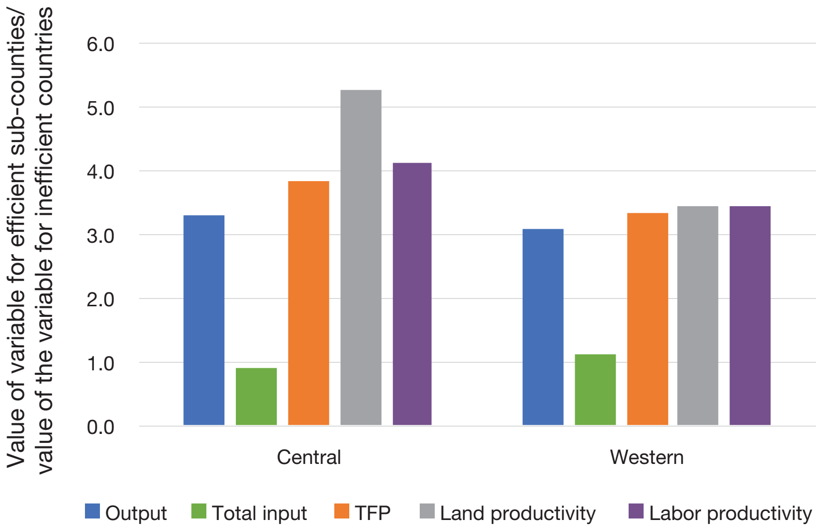
To analyze agricultural performance at the regional level, this section focuses on the main producing zones: Western, Central Highlands, and Rift Valley. As Appendix 6.2 shows, these three zones together generate 52 percent of the country's GDP, and concentrate more than 60 percent of the population, including 1.85 million farming households representing more than 70 percent of total households in agriculture. These are also the zones with the highest population density (between 138 persons per km^2 in the Rift Valley and 478 persons per km^2 in the Western zone) and the best connectivity measured in terms of the proportion of the population with access to a cell phone (between 42 percent and 57 percent) and travel time to towns of 20,000 to 100,000 people. The production unit used for the analysis is the sub-county, a decentralized unit through which the 47 county governments provide functions and services. There are in total 345 sub-counties in Kenya. Using information on the length of the growing period, sub-counties of the three zones were classified into two distinct groups. The first includes sub-counties in and around the Central Highlands and the second centers on the Western zone.[3] For the purposes of the analysis, these two groups are referred to as the Central and Western zones, respectively.

To compare and analyze performance, sub-counties in the two zones were ranked separately using the calculated values of *TFPE*. The sub-counties in the top 30 percent of this ranking were defined as "efficient performers." Sub-counties within the bottom 30 percent of the *TFPE* ranking were grouped as "inefficient performers." The remaining 40 percent were "average performers." Comparisons of different measures of output, input, productivity, input and output combination, and environmental factors were made between the groups of efficient and inefficient sub-counties.

Figures 6.7 and 6.8 present the decomposition of output into total input, TFP, and different measures of efficiency. Figure 6.7 shows values of production, input, and productivity for an average household in the efficient group of

3 As information is at the sub-county level, county limits are not followed. This means, for example, that sub-counties in neighboring counties that are not in the Central Highlands, Rift Valley, or Western zone may be included if their length of growing period (LGP) is closer to the average LGP of these zones than to the average of their county's zone. LGP is the period (in days) during a year when precipitation exceeds half the potential evapotranspiration (FAO 1978).

FIGURE 6.7 **Aggregate output, input, and productivity of efficient sub-counties measured relative to inefficient sub-counties**

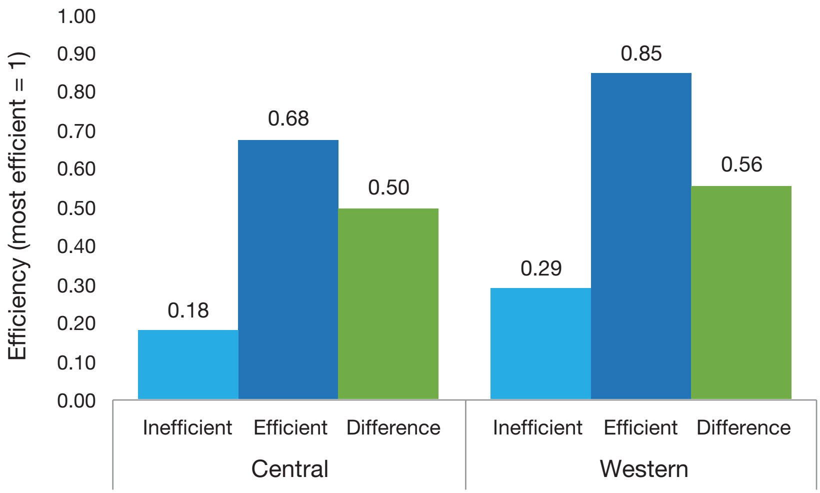


Source: Elaborated by author based on KNBS (Various years; 2006; 2019), FAO (2022), and IFPRI (2020).
Note: Values are calculated as the ratio value for efficient sub-counties divided by the value of the variable for inefficient sub-counties.

sub-counties presented as indexes, where 1 is the value of the indicator in the group of inefficient sub-counties. The average household in the efficient group in both the Central and the Western zones produces about three times more output than the average household in the inefficient group. Most of the differences in output between groups of performance in the two zones are explained by differences in *TFP*, given that differences in the total level of input used by efficient and inefficient sub-counties are small in all cases (all values are close to 1). Note that differences in land productivity in the Central zone are higher than differences in TFP and labor productivity, indicating that efficient sub-counties use more input per hectare (including labor) than inefficient sub-counties. This is not the case in the Western zone, where differences in land and labor between efficient and inefficient counties are the same as differences in TFP.

Figure 6.8 shows differences in *TFPE* for each zone. The *TFPE* of inefficient sub-counties in the Central zone is below 0.2, compared with almost 0.7 in efficient sub-counties. These differences are even larger in the Western zone, where *TFPE* of efficient sub-counties is 0.85 compared with 0.29 in inefficient sub-counties. To explain the observed differences in efficiency,

FIGURE 6.8 TFP efficiency and efficiency differences between efficient and inefficient sub-counties by agroecological zone



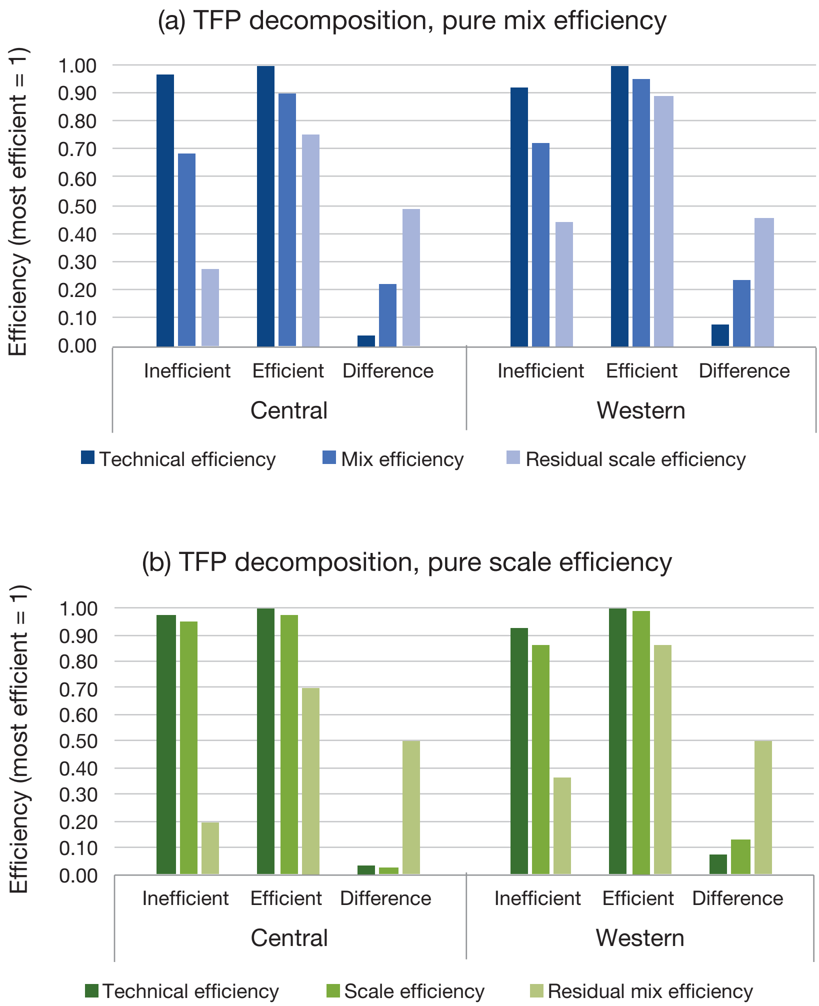
Source: Elaborated by author based on KNBS (Various years; 2006; 2019), FAO (2022), and IFPRI (2020).

Figure 6.9 displays two decompositions of *TFPE*. The first (Figure 6.9 panel A) decomposes *TFPE* into technical efficiency (*TE*), pure mix efficiency (*ME*), and residual scale efficiency (*RSE*). In Figure 6.9 panel B, *TFPE* is decomposed into the same technical efficiency as in Figure 6.9 panel A (*TE*) but the second component is now a measure of pure scale efficiency (*SE*) and the last term is a residual mix efficiency term (*RME*).

Results of the efficiency decomposition show small differences in *TE*, indicating that most sub-counties produce close to the technological frontier in their respective agroecological zones. The fact that differences in pure scale efficiency between efficient and inefficient groups are close to zero in the Central zone while showing a value of only 0.13 in the Western zone (Figure 6.9 panel B) seems to indicate that differences in scale efficiency have a small impact on overall *TFPE*. The large differences in *TFPE* observed between performance groups are primarily the result of differences in output composition and input mix and are significant only when associated with differences in the output and input mix.

To understand the effect of the use of an efficient input or output mix on overall efficiency in the two zones, Table 6.2 presents indicators of input use of efficient and inefficient sub-counties. It shows that the intensity in the use of materials per worker and hectare of cultivated land is a major factor determining

FIGURE 6.9 **Decomposition of TFP efficiency into technical, mix, scale, and residual mix-scale efficiencies and differences between efficient and inefficient sub-counties by agroecological zone**



Source: Elaborated by author based on KNBS (Various years; 2006; 2019), FAO (2022), and IFPRI (2020).

performance in the two zones. Without major differences in the use of land and labor between efficient and inefficient sub-counties within each zone, a more intensive use of materials increases outputs more than proportionally across all inputs, resulting in higher TFP. A larger proportion of irrigated area is also

TABLE 6.2 **Input use in agricultural production and differences between efficient and inefficient sub-counties by agroecological zone**

	Central				Western			
	Inefficient	Efficient	Difference	Significance	Inefficient	Efficient	Difference	Significance
Cultivated land/worker (ha)	0.4	0.3	–0.1	**	0.2	0.2	0.0	–
Animal units/worker	2.2	1.6	–0.6	–	1.7	1.6	–0.1	–
Materials/worker (KSh)	56.6	76.7	20.0	*	44.8	61.3	16.5	***
Irrigated land/1,000 workers (ha)	9.1	27.0	17.9	**	2.4	10.5	8.1	–
Total input/worker (KSh 1,000)	32.6	33.9	1.3	–	25.1	31.2	6.1	**
Animal units/ha of cultivated land	6.5	6.4	–0.2	–	8.3	7.5	–0.8	–
Materials/ha of cultivated land (KSh)	200.7	318.1	117.4	**	207.1	285.9	78.8	***
Cultivated land irrigated (%)	2.7	11.2	8.6	***	1.9	3.7	1.8	–
Total input/cultivated land (KSh)	107.8	154.0	46.3	–	121.0	141.2	20.2	–
Cultivated land/farming household (ha)	1.6	1.0	–0.7	**	1.0	1.0	0.0	–

Source: Elaborated by authors based on KNBS (Various years; 2006; 2019), FAO (2022), and IFPRI (2020).

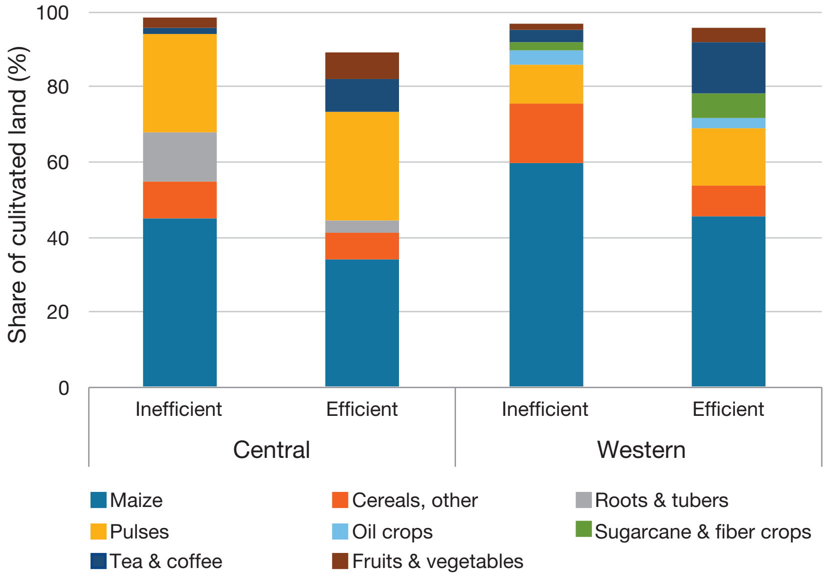
Note: * refers to the p-value from a t-test of the difference between the groups of counties with low and high levels of poverty and food insecurity: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

a major factor explaining higher TFP in best-performing sub-counties of the Central zone, where higher use of materials likely complements higher levels of irrigation. No significant differences in irrigated area are observed between best and worst performers in the Western zone, the zone with highest levels of annual precipitation in Kenya.

The mix of land and labor used in production seems to be the other major variable related to mix efficiency in the Central zone, where efficient sub-counties show only 1 ha of cultivated land per household compared with 1.6 ha among inefficient sub-counties. Significant differences are also observed in the number of hectares per worker. No differences are observed in the land–labor ratios of efficient and inefficient sub-counties in the Western zone.

Differences in the efficiency of the output mix used are analyzed by comparing land allocation with different crop activities by efficient and inefficient sub-counties. Figure 6.10 shows that efficient sub-counties in the Central zone allocate more area to cash crops and fruits and vegetables and less to staple crops than inefficient sub-counties. Inefficient sub-counties allocate on average almost 70 percent of cultivated area to staple crops and 5 percent to fruits and vegetables, and tea and coffee. Efficient sub-counties, on the other hand, allocate only 44 percent of their area to mixed staples and 17 percent to high-value crops.

FIGURE 6.10 **Allocation of cultivated land in efficient and inefficient sub-counties by agroecology**



Source: Elaborated by authors based on KNBS (various years; 2006; 2019), FAO (2022), and IFPRI (2020).

In the Western zone, the importance of maize production is reflected in the 46 percent of the cultivated area allocated to this crop by the most efficient sub-counties compared with almost 60 percent in the group of inefficient sub-counties. Overall, inefficient sub-counties in the Western zone allocate 75 percent of their land to cereals and 10 percent to cash and high-value crops (tea; fruits and vegetables; sugarcane, fiber, and oil crops) compared with 55 and 28 percent allocated to cereals, and high-value and cash crops, respectively, by efficient sub-counties.

Differences in the area allocated to different crops and differences in the yields of these crops result in higher agricultural production by efficient sub-counties, explaining most of the differences in mix efficiency observed in the *TFPE* decomposition. Table 6.3 shows that output differences between efficient and inefficient sub-counties in the Central zone are mostly the result of higher yields (52 percent) and the interaction effect between yields and differences in land allocation (40 percent). Most of this difference is explained by fruits and vegetables, roots and tubers, and tea. In the Western zone, yields explain 45 percent of the difference in crop production between efficient and

TABLE 6.3 Contribution of yield and area of different crops to differences in total crop output between efficient and inefficient sub-counties by agroecology (%)

	Central				Western			
	Yield	Area	Yield–area interaction	Total	Yield	Area	Yield–area interaction	Total
Maize	8.2	–0.7	–2.0	–	14.4	–2.4	–3.3	8.7
Cereals, other	3.0	–0.4	–1.3	1.2	4.4	–1.2	–1.5	1.7
Roots and tubers	12.5	2.8	8.1	23.4	5.5	1.5	3.2	10.2
Pulses	7.9	0.2	0.9	9.0	4.9	1.4	2.4	8.7
Sugarcane, oil, and fiber crops	4.7	–0.9	–4.4	–0.6	3.7	6.6	3.9	14.1
Tea	1.5	2.9	8.3	12.7	7.7	4.2	23.4	35.3
Coffee	0.8	0.3	2.2	3.3	0.0	0.1	0.1	0.3
Fruits and vegetables	13.3	4.0	28.1	45.4	3.9	10.1	7.1	21.1
Total	51.8	8.2	40.0	100.0	44.5	20.3	35.2	100.0

Source: Elaborated by authors.

inefficient sub-counties while differences in land allocation contribute to 20 percent of differences in total output, with yield–land interactions explaining the remaining 35 percent. Tea, fruits and vegetables, roots and tubers, and cash crops (oil and fiber crops and sugarcane) explain most production differences between efficient and inefficient sub-counties in this zone.

Finally, Table 6.4 compares the value of different indicators related to the production environment of efficient and inefficient sub-counties. In the case of the Central zone, efficient sub-counties show a more diversified economy, where agriculture represents less than 50 percent of country GDP and where greater access to mobile phones is expected to be related to better infrastructure and a more diversified economy. Shorter travel time to towns of 20,000 is used as an indicator of better access to local markets. No differences are observed in access to the internet, travel time to larger markets, access to credit, employment in agriculture, or education.

There are no major differences between inefficient and efficient sub-counties in the Western zone. Efficient sub-counties appear to have better access to larger markets (towns of 250,000) but the differences are small and significant only at the 10 percent level. Also, small differences are observed in the percentage of the population with access to credit, where access is higher in inefficient sub-counties. A possible explanation for this is that households use access to credit to diversify income into nonagricultural activities, which could explain the importance of maize and staple crops and the less commercial orientation of production systems in inefficient sub-counties.

TABLE 6.4 **Differences in the value of indicators of production environment in efficient and inefficient sub-counties by agroecology**

	Central				Western			
	Inefficient	Efficient	Difference	Significance	Inefficient	Efficient	Difference	Significance
Length of growing period	242	230	–12	–	298	298	0.6	–
Access to mobile phone (%)	46.8	55.2	8.4	**	42.7	42.3	–0.4	–
Access to internet (%)	21.1	23.4	2.3	–	16.1	16.4	0.3	–
Travel time to towns of 20,000	1.5	1.1	–0.5	**	0.7	0.8	0.1	–
Travel time to towns of 250,000	2.1	2.2	0.1	–	3.8	3.4	–0.4	*
Access to credit (% of population)	28.5	27.6	–0.9	–	42.2	34.2	–8.0	*
Share of agriculture in county GDP (%)	62.6	48.9	–13.7	***	48.5	51.6	3.1	–
Employment in agriculture (%)	69.2	73.8	4.6	–	84.0	84.3	0.3	–
Population with primary education (%)	40.7	43.5	2.7	–	44.6	44.9	0.3	–
Population with secondary education (%)	19.7	21.7	2.0	–	18.9	18.5	–0.4	–

Source: Elaborated by authors based on KNBS (various years; 2006; 2019), FAO (2022), and IFPRI (2020).

Note: * refers to the p-value from a t-test of the difference between the groups of counties with low and high levels of poverty and food insecurity: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

In sum, efficient sub-counties in the Central and Western zones allocate a larger share of harvested area to export and high-value crops and a lower share of this area to maize and other staple crops. Efficient sub-counties in the two zones show a positive correlation between higher intensity in the use of materials per worker and hectares of cultivated land, with efficiency in land allocation. Efficient sub-counties in the Central zone also show a larger proportion of irrigated area than do inefficient sub-counties. As a result of these differences, the average household in the efficient group in both the Central and Western zones produces about three times more output than the average household in the inefficient group, while *TFP*, land, and labor productivity in efficient sub-counties are at least three times bigger than in inefficient sub-counties. Output differences between efficient and inefficient sub-counties in the Central zone are mostly the result of higher yields of fruits and vegetables, roots and tubers, and maize and the interaction between higher yields and differences in land allocation. In the Western zone, output differences result from larger areas allocated to fruits and vegetables, tea, and other cash crops, and higher yields in almost all crops but especially in maize and tea. There is some evidence showing that efficient sub-counties in the Central zone are part of counties with a more diversified economy, better infrastructure, and better access to local markets.

No major differences were observed in the economic environment of sub-counties in the Western zone; however, better access of the population to credit and longer travel time to larger markets in inefficient sub-counties could be related to the less commercial orientation of production systems in these sub-counties.

Two interpretations of results, and policy implications

Policy changes in the past two decades have had some success in the medium run, improving the performance of Kenya's agriculture as shown in Figures 6.1 and 6.2. After poor performance between 2000 and 2007, explained in part by adverse climatic conditions, followed by a prolonged severe drought between 2008 and 2011, agricultural production started its recovery in 2010, with farmers increasing the use of materials per hectare, land productivity, and TFP. These improvements did not yield benefits in terms of labor productivity, however (Figure 6.3). With the population projected to double by 2050 with respect to its level in 2020, food production and agricultural exports will need to sustain fast growth and increase their value added in the next 30 years to avoid further deterioration of the country's trade food balance.

The results of the regional analysis give some insights on the challenges Kenya faces in sustaining fast agricultural growth in the future. They show that the more productive sub-counties in and around the Central and Western zones are more market-oriented; use more inputs per worker and hectare; allocate more land to fruits and vegetables, tea and coffee, and other cash crops; and obtain much higher yields from these activities and from maize and other staples than do inefficient sub-counties. Efficient sub-counties in the Central zone also show a smaller average farm area, a higher proportion of irrigated area, and a smaller cultivated area than do inefficient sub-counties.

At least two possible interpretations of these results can be made, with very different policy implications. The first interpretation could use results showing that sub-counties with smaller farm areas are more efficient and productive than sub-counties with more land available as a confirmation of the inverse relationship between farm size and productivity frequently observed in Africa. Assuming higher efficiency of smallholders, policies under this interpretation would target smaller, efficient farms (those cultivating 1 ha or less as shown in Table 6.2) with extensive interventions in markets and support services—extension, subsidies to inputs, investment in irrigation schemes, roads—to favor the use of improved crop varieties and the intensive use of fertilizer and labor per hectare (Collier and Dercon 2014). In the case of Kenya, the goal of these policies would be to close the productivity gap between efficient and inefficient sub-counties. This interpretation has been supported by donors and adopted by several African governments, which have spent large shares of their budgets on subsidies for technology adoption. However, little evidence of widespread progress in technology adoption and productivity growth has been observed so far (Wise 2020), particularly in Kenya.

A second interpretation of the results is based on significant evidence from the most recent literature. Under this interpretation, the inverse relationship between area and productivity is flawed because of the aggregation used and the small variability between sub-counties in average farm size. Muyanga and Jayne (2019) tested the inverse relationship hypothesis on a much wider range of farm sizes than in most studies and found that farms between 20 and 70 ha were substantially more productive than farms under 5 ha. Results like these are a major challenge to the hypothesis of efficient smallholders as agents of change and of the transformation of agriculture by facilitating farmers' access to new technologies. Rather than an indication of efficiency, the small size of farms in Kenya could be part of a poverty trap whereby frictions in land markets prevent households from exiting agriculture to the extent that would be efficient (see, for example, Chen 2017; Gottlieb and Grobov 2019; discussion in Gollin 2021). Spatial frictions that alter crop choice, affect input use, and prevent local specialization could also be behind the differences observed between the Central and Western zones, as the Western zone lags the Central zone in income per capita, specialization in cash crops, and diversification of its economy, with a higher share of agriculture in county GDP and labor markets.

In this context, an explanation of low agricultural productivity in Africa that has received considerable attention in recent years is that there are simply too many farmers (Gollin 2021). With more than half of the adults in Kenya earning their living from agriculture, it seems plausible that not all are equally capable. Gollin (2021) argues that, with well-functioning markets, the least effective farmers would be expected to move out of agriculture into other occupations, either selling or renting their land to farmers who are more skillful. That this is not happening could imply that Kenya may have institutional frictions or rigidities that prevent unproductive farmers from exiting the market (see discussion and references in Gollin 2021). The outcome is aggregate inefficiency resulting from the misallocation of labor, capital, and managerial effort that creates a consequential drag on aggregate productivity. Studies by Chen (2017), Restuccia and Santaeulalia-Llopis (2017), and Gollin and Udry (2021) point in this same direction, finding that misallocation could not only lead to substantial losses in aggregate efficiency and sizable reductions in overall agricultural output but also prevent efficient allocation of resources across sectors as a result of frictions in land markets. Muraoka, Jin, and Jayne (2015) show that, in Kenya, land rental markets are the most important means available to land-constrained rural households to access additional land for cultivation even when rental markets perform below their potential. Muraoka and colleagues conclude that there appears to be untapped potential for land rental markets to play a positive role in promoting agricultural production and food security in rural Kenya in the future.

The implications for investment and technical change of the "land market frictions" interpretation is that land constraints mean there is little incentive to invest the careful and timely attention to agronomic management needed for the efficient use of fertilizer. Instead, most vulnerable households sell labor and land and diversify income to off-farm sources to minimize risks. Smallholders following this strategy are unlikely to intensify their production, which limits their ability to contribute to their own, or national, food self-sufficiency. There are also few incentives for intensification where land is more abundant. Particularly if animal traction is available, households are predisposed to increase their production by cultivating more land, through extensification, rather than through increasing yields, which has happened in Kenya (as De Groote, Marangu, and Gitonga 2020 have shown). Better-endowed households, on the other hand, have tended to diversify and acquire land that has enabled them to adapt to and benefit from the major changes observed in external drivers. This could have happened more often in efficient sub-counties in the Central zone but no information is available on the distribution of land by farm size.

Under the "land market frictions" interpretation of the results, the implementation of policies and institutions that support a better allocation of resources in the agriculture sector is critical to allow farms to grow and become economically *and* agronomically viable while keeping the urban population well fed. The efficient reallocation of factors and the increase in productivity that could result from these policies would encourage productive farmers to invest and grow by using modern inputs (mechanization, chemical seeds, and other intermediate inputs) and by investing in better farm management practices, triggering a profound process of structural transformation (Adamopoulos and Restuccia 2014; Chen et al. 2021a).

Further analysis is needed to define specific policies that could deliver the transformation of Kenya's agriculture under the second interpretation of the productivity results obtained here, but some policy areas seem to be relevant given the evidence so far. First, to facilitate the reallocation of land and other factors of production to more productive uses, Chen, Restuccia, and

Santaeulalia-Llopis (2021b) point to the need for well-defined property rights over land and the development of well-functioning land and complementary markets. In this regard, Chen and colleagues present the examples of a property rights reform associated with digitization of land titles in Pakistan (Beg 2022), a rural land contracting law in China that formalizes leasing rights (Chari et al. 2021), and a land certification reform in Ethiopia (Chen et al. 2021a). In all these cases, the reform induces more land rental activity that improves resource allocation and productivity in the agriculture sector. Reallocation of inputs also results in reductions in agricultural income inequality and poverty because the poorest agricultural households happen to be the least productive and hence benefit the most from secure property rights and the rental income associated with an efficient allocation (Chen et al. 2021b).

A second set of policies includes measures to support the emerging commercial farmers who are expected to foster labor productivity growth, wage labor income, and integration in retail value chains toward domestic and export markets. Also relevant are policies and investments to shape the development of the industrial structure of the food and agriculture sector and the links at different levels of the value chain (Neven et al. 2009 for horticulture and supermarkets in Kenya; Lowder, Skoet, and Raney 2016).

A third relevant policy area includes policies and institutions to facilitate the movement of labor out of agriculture and into nonagricultural sectors in this process. This further requires the creation of rural and urban jobs in industry and services and other forms of social protection in the form of social safety nets.

Finally, it seems to be particularly relevant for Kenya to obtain a better understanding of the drivers of agricultural growth, and the role of the domestic market, agricultural exports, and the agro-processing industry. As stated by Gollin (2021), one lesson that emerges from the literature is that there is substantial heterogeneity in agriculture's role in structural transformation, across both geographical contexts and time, and depending critically on the nature of demand for agricultural goods. Could agricultural exports of tea, coffee, fruits, and vegetables—the most dynamic activities in agriculture—drive growth and transformation of the Kenya's economy? Is there a role for the shrinking manufacturing sector to play? Could a more productive agriculture sector trigger growth and transformation of the food industry sector? Chapter 2 of this book provides some initial estimates but more research is needed to answer these questions, to better understand the reasons behind slow productivity growth, and to identify the most appropriate policies and pathways for the transformation of Kenya's agriculture.

Appendix 6.1 Productivity index

The Lowe index used to calculate TFP satisfies several properties of index numbers needed to make sound comparisons of production units across time and/or space. The property of most interest for the analysis in this study is the transitivity property. An index is transitive if the index number that directly compares the TFP of a sub-county (or a year) with the TFP of a reference sub-county (or reference year) is identical to the index number computed when the comparison is made through an intermediate sub-county (or year). This means that, if an TFP index is transitive*, then* if $TFP_A > TFP_B$ and $TFP_B > TFP_C$ then $TFP_A > TFP_C$. Indexes like the Fisher, Tornqvist, and Malmquist do not satisfy the transitivity property, so it is possible to have $MPF_A < TFP_C$ *in the comparison even when* $TFP_A > TFP_B$ and $TFP_B > TFP_C$.

Explaining differences in TFP between sub-counties in Kenya involves estimating measures of differences in technology and in efficiency. For this purpose, the TFP index in Equation 2 in the main text, comparing sub-counties A and h, can be exhaustively decomposed into different measures of efficiency. In what follows, the efficiency decomposition of TFP is presented using Figure A6.1 as the reference.[4] The figure depicts values of aggregated input (horizontal axis) and aggregated output (vertical axis) while point *A* represents a production unit (for example, a sub-county) producing total output Q_A using aggregated input X_A. The definition of TFP as the ratio of an aggregated output and an aggregated input can be used here to determine TFP_A as the slope of the line going from the origin to point *A*. The steeper the slope of the line *OA*, the higher the TFP_A.

Production unit *A* produces under an available technology defined as all the points to the right and below the full curve passing through point *E,* the production frontier. This frontier envelopes all aggregate input–output feasible combinations that can be produced with the available technology. No production unit can produce to the left or above this frontier. The point of maximum feasible TFP, given the observed technology, is determined by the line with the biggest slope passing through the origin and a technically feasible point. In Figure A6.1, the maximum value of TFP is given by $TFP^* = Q^*/X^* = slope\ OE$. $TFPE_A$ is then defined as the ratio of *A*'s *TFP* and the maximum *TFP* given the available technology:

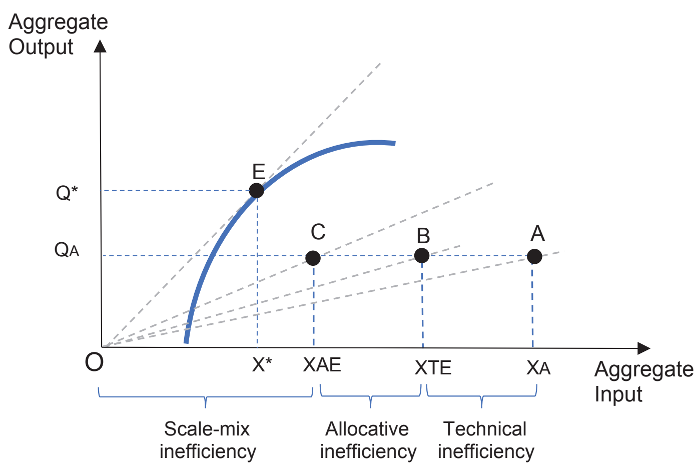
$$MFPE_A = \frac{MFP_A}{MFP^*} = \frac{Q_A}{X_A} \times \frac{X^*}{Q^*} = \frac{slope\ OA}{slope\ OE} \qquad \text{A1}$$

4 To simplify notation, in what follows $Q_A = Q_{hA} = Q(q_A)/Q(q_h)$; $X_A = X_{hA} = X(x_A)/X(x_h)$, $MFP_A = MFP_{hA}$.

To proceed with the full decomposition of differences in *TFPE*, it is necessary to identify the reference points with which unit *A* is to be compared to obtain measures of pure technical efficiency (TE_A), mix efficiency (ME_A), and the residual scale efficiency (RSE_A). The first of these points is production unit B in Figure A6.1. *B* produces the same quantity and combination of outputs as unit *A* but uses less input ($X_B<X_A$), which means it is more technically efficient than A. The "pure" technical efficiency component of $TFPE_A$ is then calculated as:

$$MFPE_A = \frac{MFP_A}{MFP^*} = \frac{Q_A}{X_A} \times \frac{X^*}{Q^*} = \frac{slope\ OA}{slope\ OE} \qquad \text{A2}$$

FIGURE A6.1 Measures of efficiency in aggregate output–input space



Source: Adapted from O'Donnell (2012).

Comparing production unit A against a unit producing the same output but using a different combination of inputs, as is the case with production unit C in Figure A6.1, the result is a measure of allocation efficiency of inputs (XAE). In other words, XAE in Figure A6.1 is the minimum value of aggregated input needed to produce Q_A quantities of output. *A* can produce Q_A using quantities XAE of aggregated input only if it employs the mix of inputs used by C. The "pure" mix efficiency of *A* in Figure A6.1 is calculated as:

$$ME_A = \frac{Q_A}{XTE} \times \frac{XAE}{Q_A} = \frac{XAE}{XTE} = \frac{slope\ OB}{slope\ OC} \qquad \text{A3}$$

Finally, the difference between *A*'s *TFP* and the maximum *TFP* after accounting for pure technical change and mix efficiency is the residual scale efficiency, which requires changes in X_A together with changes in the mix of outputs and inputs:

$$RSE = \frac{Q_A}{XAE} \times \frac{X^*}{Q^*} = \frac{slope\ OC}{slope\ OE} \qquad \text{A4}$$

Putting all together, *Equation 4* can now be expressed in terms of the full *TFP* decomposition:

$$MFP_A = MFP^* \times \frac{XTE}{X_A} \times \frac{XAE}{XTE} \times \frac{Q_A}{XAE} \times \frac{X^*}{Q^*} = MFP^* \times \frac{Q_A}{X_A} \times \frac{X^*}{Q^*} = MFP^* \times MFPE_A \qquad \text{A5}$$

Or, equivalently:

$$MFP_A = MFP^* \times TE_A \times ME_A \times RSE_A \qquad \text{A6}$$

Equation A6 shows that TFP can be exhaustively decomposed into a measure of technology (the maximum TFP that can be achieved with the available technology) and a measure of efficiency change that can be further decomposed into technical, mix, and a residual scale efficiency terms.

The efficiency measures derived from Figure A6.1 are what the literature refers to as "*input-oriented efficiency*," as it involves finding the minimum potential input for a given amount of output. In a similar fashion, output-oriented efficiency measures could be obtained by finding the largest output set that can be produced by a fix amount of input (see Figure 5 in O'Donnell 2012). Furthermore, O'Donnell (2012) shows that the same approach can be used to decompose the efficiency change component into any number of meaningful output- or input-oriented measures. For example, a TFP index can be decomposed into measures of technology, pure technical efficiency, pure scale efficiency, and a residual mix efficiency, instead of the pure mix efficiency and residual scale efficiency derived here. For the analysis in this study, a geometric mean of the output- and an input-oriented versions of Equation A6 is used in the reported results.

Appendix 6.2 Kenya's agroecologies

TABLE A6.1 Kenyan agroecological zones as defined by the Agricultural Sector Transformation and Growth Strategy

Western	Moderate to deep red soils of medium–high fertility and two seasons of medium rains Mixed staples and cash crops including maize, French beans, sugar cane, groundnuts, sweet potatoes, Irish potatoes, dairy, poultry, and a variety of fish species
Rift Valley	Mixed shallow/low with deep/highly fertile soils and one season of moderate rainfall Mixed staples, cash crops, and livestock, including maize, wheat, sorghum, Irish potatoes, honey, goats, sheep, chicken, and dairy cattle
Central Highlands	Deep red highly fertile soils and two seasons of high rainfall Cash crops, including coffee, tea, Irish potatoes, French beans, bananas, tomatoes, and other staples, including dairy, cattle, and poultry
Semiarid uplands	Red, acidic, low to moderately fertile soils, with one season of low rains Dryland crops such as sorghum and pigeon peas, and beef cattle
Northern ASALs	Sandy, saline, shallow, low-fertility soil with one season of rain at best Livestock pastoralism, including camels, goats, and sheep, with occasional maize cultivation on raised plateaus
Central ASALs	Saline, low-fertility soils, with one season of rain at best Livestock pastoralism, including beef, cattle, goats, and sheep, with occasional maize cultivation on raised plateaus
Coast	Mix of sandy, deep, low, and highly fertile soil and two seasons of moderate rainfall Mixed staples and cash crops, including maize, sorghum, millet, cashew nuts, mangoes, marine fish, crustaceans and mollusks, and poultry

Source: Kenya, Ministry of Agriculture (2018).

TABLE A6.2 Characterization of Kenya's agroecologies and major urban centers

	North ASALS	Central ASALS	Semi-arid Uplands	Coast	Rift Valley	Central Highlands	Western	Mombasa-Nairobi	KENYA
Structural									
GCP per capita (2019 KSh)	37,103	50,962	80,510	56,035	91,502	97,963	71,339	234,274	93,471
Share in GCP	3	3	8	3	8	17	28	30	100
Agriculture (% of GCP)	45	29	20	26	41	35	36	0	24
Agricultural labor (% employment)	50	60	61	58	61	54	76	0	71
Infrastructure									
Persons with cell phone (%)	23	38	49	38	42	57	42	68	47
Travel time to towns of 20K people	6.3	3.4	2.3	2.8	1.9	1.0	0.9	–	1.9
Travel time to towns of 100K people	10.5	4.8	3.3	3.4	2.7	2.3	1.8	–	3.1
Travel time to towns of 500K people	14.2	6.8	3.6	3.4	4.5	2.8	5.4	–	5.5
Education									
Primary education (%)	13	26	42	41	38	41	44	30	38
Secondary education (%)	4	11	20	11	18	24	19	28	19
Population									
Rural population (%)	77	78	73	77	69	68	86	0	70
Total population ('000)	3,035	2,900	4,373	2,465	3,987	7,421	16,781	5,605	46,568
Persons per square km.	17	31	110	81	138	368	478	5,871	82
Share of total population	7	6	9	5	9	16	36	12	100
Number of households ('000)	496	627	1,233	510	1,000	2,281	3,919	1,885	12,144
Farming households (%)	18	23	23	23	23	22	29	1	21
Household size	6.1	4.6	3.5	4.8	4.0	3.3	4.3	3.0	3.8

Source: Elaborated by authors based on Kenya, Ministry of Agriculture (2018) and KNBS (various years).
Note: GCP is gross county product.

References

Adamopoulos, T., and D. Restuccia. 2014. "The Size Distribution of Farms and International Productivity Differences." *American Economic Review* 104 (6): 1667–1697.

Alila, P.O., and R. Atieno. 2006. "Agricultural Policy in Kenya: Issues and Processes." Paper prepared for the Future Agricultures Consortium Workshop, Institute of Development Studies, March 20–22.

ASTI (Agricultural Science and Technology Indicators). 2021. ASTI database. Accessed February, 2021. https://asti.cgiar.org/

Balié, J., P. Boulanger, A. Mainar Causapé, H. Dudu, E. Ferrari, and L. Battaglia. 2018. *Policy Options to Support the Agriculture Sector Growth and Transformation Strategy in Kenya: A CGE Analysis*. Luxembourg: European Commission, Joint Research Centre.

Beg, S. 2022. "Digitization and Development: Property Rights Security, and Land and Labor Markets." *Journal of the European Economic Association* 20 (1): 395–429.

Beintema, N., L. Mose, T. Kibet, R. Emongor, F. Murithi, I. Kimani, V. Ndungu, and P. Mwangi. 2018. *Kenya: Agricultural R&D Indicators Factsheet Update*. Washington, DC: International Food Policy Research Institute (IFPRI); Nairobi: Kenya Agricultural and Livestock Research Organization (KALRO).

Birch, I. 2018. *Agricultural Productivity in Kenya: Barriers and Opportunities*. K4D Helpdesk Report. Brighton, UK: Institute of Development Studies.

Chari, A., E.M. Liu, S.Y. Wang, and Y. Wang. 2021. "Property Rights, Land Misallocation, and Agricultural Efficiency in China." *Review of Economic Studies* 88 (4): 1831–1862.

Chen, C. 2017. "Untitled Land, Occupational Choice, and Agricultural Productivity." *American Economic Journal: Macroeconomics* 9 (4): 91–121.

Chen, C., D. Restuccia, and R. Santaeulalia-Llopis. 2021a. "The Effects of Land Markets on Resource Allocation and Agricultural Productivity." *Review of Economic Dynamics* 45: 41–54.

Chen, C., D. Restuccia, and R.Santaeulalia-Llopis. 2021b. "Land Misallocation and Productivity." NBER Working Paper 23128. National Bureau of Economic Research, Cambridge, MA.

Collier, P., and S. Dercon. 2014. "African Agriculture in 50 Years: Smallholders in a Rapidly Changing World?" *World Development* 63: 92–101.

De Groote, H. 2022. "Intensification of the Maize Systems in Kenya with Improved Varieties and Fertilizer: What Happened to the Maize Green Revolution?" Unpublished paper.

De Groote, H., C. Marangu, and Z.M. Gitonga. 2020. "Evolution of Agricultural Mechanization in Kenya." In *An Evolving Paradigm of Agricultural Mechanization Development: How Much Can Africa Learn from Asia?* Eds. X. Diao, H. Takeshima. and X. Zhang, 401–422. Washington, DC: IFPRI.

De Groote, H., and L.B. Omondi. 2021. “Adoption of Improved Maize Varieties, Varietal Turn-over and Their Effect on Yield and Food Security-Evidence from Four Household Surveys Over 20 Years in Kenya.” Paper presented at the 31st Virtual International Conference of Agricultural Economists (ICAE), August 17–31.

FAO (Food and Agriculture Organization of the United Nations). 1978. *Report on the Agro-ecological Zones Project, Vol. 1: Results for Africa.* World Soil Resources Report 48/1. Rome: FAO.

FAO. 2022. FAOSTAT database. Accessed February 8, 2022. http://faostat.fao.org.

Gollin, D. 2021. *Agricultural Productivity and Structural Transformation: Evidence and Questions for African Development*. STEG Pathfinding Paper. London: Foreign, Commonwealth and Development Office (FCDO).

Gollin, D., and C. Udry. 2021. “Heterogeneity, Measurement Error, and Misallocation: Evidence from African Agriculture.” *Journal of Political Economy* 129 (1): 1–80.

Gottlieb, C., and J. Grobov. 2019. “Communal Land and Agricultural Productivity.” *Journal of Development Economic* 138: 135–152.

IFPRI (International Food Policy Research Institute). 2020. “Spatially-Disaggregated Crop Production Statistics Data in Africa South of the Sahara for 2017.” Harvard Dataverse, V3.

Jayne, T. S., N.M. Mason, W.J. Burke, and J. Ariga. 2018. “Taking Stock of Africa’s Second-Generation Agricultural Input Subsidy Programs.” *Food Policy* 75: 1–14.

Jena, P.R., H. De Groote, B.P. Nayak, A. Hittmeyer. 2021. “Evolution of Fertiliser Use and Its Impact on Maize Productivity in Kenya: Evidence from Multiple Surveys.” *Food Security* 31: 95–111.

Kenya, Ministry of Agriculture. 2010. *Agricultural Sector Development Strategy 2010–2020*. Nairobi.

Kenya, Ministry of Agriculture. 2018. *Agricultural Transformation and Growth Strategy: Towards Sustainable Agricultural Transformation and Food Security in Kenya*. Nairobi.

Kenya, Ministry of State Planning. 2007. *Kenya Vision 2030: The Popular Version*. Nairobi.

Kibaara, B., J. Ariga, J. Olwande and T.S. Jayne. 2008. Trends in Kenyan Agricultural Productivity: 1997–2007. WPS 31/2008, Tegemeo Institute of Agricultural Policy and Development, Nairobi.

Kimenyi, M., F.M. Mwega, and N. Ndung’u. 2015. “The African lions: Kenya Country Case Study.” UNU-WIDER Working Paper No. 2015/134. UNU-WIDER, Helsinki.

Kirori, G.N. 2003. “Rural Development Policies in Kenya: A Critical Analysis.” Master’s thesis, Department of Economics, University of Nairobi.

KNBS (Kenya National Bureau of Statistics). Various years. *Economic Survey*. Nairobi.

KNBS. 2019. *2019 Kenya Population and Housing Census, Volume IV: Distribution of Population by Socio-economic Characteristics*. Nairobi.

KNBS. 2006. *Kenya Integrated Household Budget Survey 2005/06*. Basic report. Nairobi.

KNBS. 2020. *Children, Youth, Women, Men & the Elderly: From National to County Level*. Comprehensive Poverty Report. Nairobi.

Lowder, S.K, J. Skoet, and T. Raney. 2016. "The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide." *World Development* 87: 16–29.

Muraoka, R., S. Jin, and T.S. Jayne. 2015. "Land Access, Land Rental and Food Security: Evidence from Kenya." Paper presented at the International Conference of Agricultural Economists (ICAE), Milan, Italy, August 8–14.

Mutsotso, R.B., A.W. Sichangi and G.O. Makokha. 2018. "Spatio-Temporal Drought Characterization in Kenya from 1987 to 2016." *Advances in Remote Sensing* 7: 125–143.

Muyanga, M., and T.S. Jayne. 2019. "Revisiting the Farm Size-Productivity Relationship Based on a Relatively Wide Range of Farm Sizes: Evidence from Kenya." *American Journal of Agricultural Economics* 101 (4): 1140–1163.

Mwega, F.M., and N.S. Ndung'u. 2008. "Explaining African Economic Growth Performance: The Case of Kenya." In *The Political Economy of Economic Growth in Africa, 1960–2000. Volume 2: Country Case Studies*, eds. B.J. Ndulu, S.A. O'Connell, J.-P. Azam, R.H. Bates, A.K. Fosu, J.W. Gunning, and D. Njinkeu. Cambridge: Cambridge University Press.

Neven, D., M.M. Odera; T. Reardon, and H. Wang. 2009. "Kenyan Supermarkets, Emerging Middle-Class Horticultural Farmers, and Employment Impacts on the Rural Poor." *World Development* 37 (11): 1802–1811

Nyoro, J., and T.S. Jayne. 1999. "Trends in Regional Agricultural Productivity in Kenya." Paper presented at the Kenya Agricultural Monitoring and Policy Analysis Project Conference Proceedings, July 1999. Tegemeo Institute, Nairobi.

O'Donnell, C.J. 2012. "Nonparametric Estimates of the Components of Productivity and Profitability Change in U.S. Agriculture." *American Journal of Agricultural Economics* 94 (4): 873–890.

Onjala, J.O. 2002. *Total Factor Productivity in Kenya: The Links with Trade Policy*. AERC Research Paper 118. Nairobi : African Economic Research Consortium.

Poulton, C., and K. Kanyinga. 2014. "The Politics of Revitalising Agriculture in Kenya." *Development Policy Review* 2 (32): 151–172.

Restuccia, D., and R. Santaeulalia-Llopis. 2017. "Land Misallocation and Productivity." Technical Report. Cambridge, MA: National Bureau of Economic Research.

Wamalwa, P.S., and M. Were. 2021. "Is it Export- or Import-Led Growth? The Case of Kenya." *Journal of African Trade* 8 (1): 33–50.

Wanyama, R., M.W.K. Mathenge, and Z.S. Mbaka. 2016. Agricultural Information Sources and Their Effect on Farm Productivity in Kenya." Tegemeo Institute of Agricultural Policy and Development, WPS 62/2016.

Wise, T.A. 2020. "Failing Africa's Farmers: An Impact Assessment of the Alliance for a Green Revolution in Africa." Working Paper 20-01. Global Development and Environment Institute, Medford, MA.

World Bank. 2019. *Unbundling the Slack in Private Sector Investment: Transforming Agriculture Sector Productivity and Linkages to Poverty Reduction*. Kenya Economic Update, Edition No. 19. Washington, DC.

World Bank. 2022. World Development Indicators. Accessed February 2022. https://data.worldbank.org/country/KE

World Bank. 2023. The World Bank in Kenya. Last updated March 31, 2023. https://www.worldbank.org/en/country/kenya/overview